Open Deep Learning Student Projects in our Lab

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General points

- Flexible scope for most projects:
  - OK for BSc theses or MSc projects/theses
- All projects are very up-to-date
  - State-of-the-art research topics
  - **Successful projects can lead to publications**
    (typically requires some more work afterwards, though)
- **Team work recommended for MSc projects**
  - 2-3 students per team (max. 4)
  - You can get a lot more done
  - Often, team work is more efficient & rewarding
- MSc theses typically only after a MSc project in our group

Main Topics for Projects

1. Modelling Data (with Neural Networks)
2. Bayesian Optimization
3. Multiple Fidelities
4. Benchmarking
5. AutoML: Architecture Search & HPO for Deep Learning
6. Optimization of Neural Networks
7. Learning to Learn

1. Modelling Data (with Neural Networks)

- Performance of scikit-learn classifiers & hyperparams
  - We would like to fit a good model to the data we collected
  - Handle conditional hyperparameters
  - Handle learning across data set (multi-task / meta-learning)
- Predicting learning curves
  - Extend work from existing MSc thesis
  - Superset of course project
- Horizon price:
  - http://ec.europa.eu/research/horizonprize/index.cfm?prize=bigdata / http://ec.europa.eu/research/horizonprize/bigdata
  - Learning from geospatial temporal data; forecasting electricity grid traffic; 6h time-limit → probably not deep learning

2. Bayesian Optimization

- Comparing an implementation of another acquisition function (called “knowledge gradient“) to our work
- Evaluate an implementation of approximate Gaussian processes (GPs) for Bayesian optimization
- In general:
  - There‘s a fairly steep learning curve in BO
  - Therefore, these two projects would focus more on evaluations & combining existing methods

3. Multiple Fidelities

- There are many ways to approximate a blackbox function
  - Initial learning curves
  - Subsample of dataset
  - Downsampled images
  - …

- So far, HB and BO-HB can only exploit either one of these
  - We'd like to exploit many of these multiple fidelities:
    e.g., short runs on a subsample of downsampled images
  - Of course, the goal is still to find a configuration that is good for long runs on all full-sized images
  - Simple approaches might do well (like Hyperband did);
    potentially could be improved by a model later (like BO-HB)

4. Benchmarking

- Benchmarking of hyperparameter optimization (HPO) or neural architecture search (NAS) algorithms is a problem
  - A benchmark is the combination of a code base and a dataset
    - But everyone just reports, e.g., their performance on CIFAR
    - The code base (which optimizer was used, with which regularization and dozens of other tricks) is a very strong confounding factor

- Solution: create a collection of benchmarks that includes both code and datasets
  - We have a preliminary version: HPOlib2
  - We also need to include multi-fidelity benchmarks
  - Use this to cleanly benchmark different HPO / NAS algorithms

4. Benchmarking

- Project: create better **surrogate benchmarks**
  - We collect a lot of performance data with different configurations
    - E.g., their entire learning curves; this is expensive
  - We then fit a model to these to create a new "surrogate" benchmark
    - Model predictions are cheap
    - These are all that is needed for running a hyperparameter optimizer
  - With these, we can benchmark hyperparameter optimizers in seconds instead of days
    - This provides a solid foundation for rigorous experiments in the field

4. Benchmarking

- Evaluating neural nets vs. other ML algos as dataset size increases
  - Is it really the case that they do scale better?
  - Is it really the case that for small data sets other algorithms perform better
    - Or do we just need to find the right regularization?

- Hyperparameter importance of neural networks
  - Which hyperparameters are most important?
  - Which hyperparameters have correlated effects?
  - What are good ranges for the hyperparameters?
  - Can we learn a mapping from dataset characteristics to good hyperparameter settings?

5. Auto-Net: NAS & HPO for Deep Learning

- Auto-Net is not yet at the level of an easy-to-use tool
  - Parameterization of a space of networks in TensorFlow

- Possible projects:
  - Implement different regularization methods / evaluate them for ParamNet
  - Study how well neural networks work on small datasets
  - Actually create an Auto-Net tool that is easy to use
  - With Bosch:
    - current NAS methods focus on classification / regression
    - extend this work to semantic segmentation

6. Optimization of Neural Networks

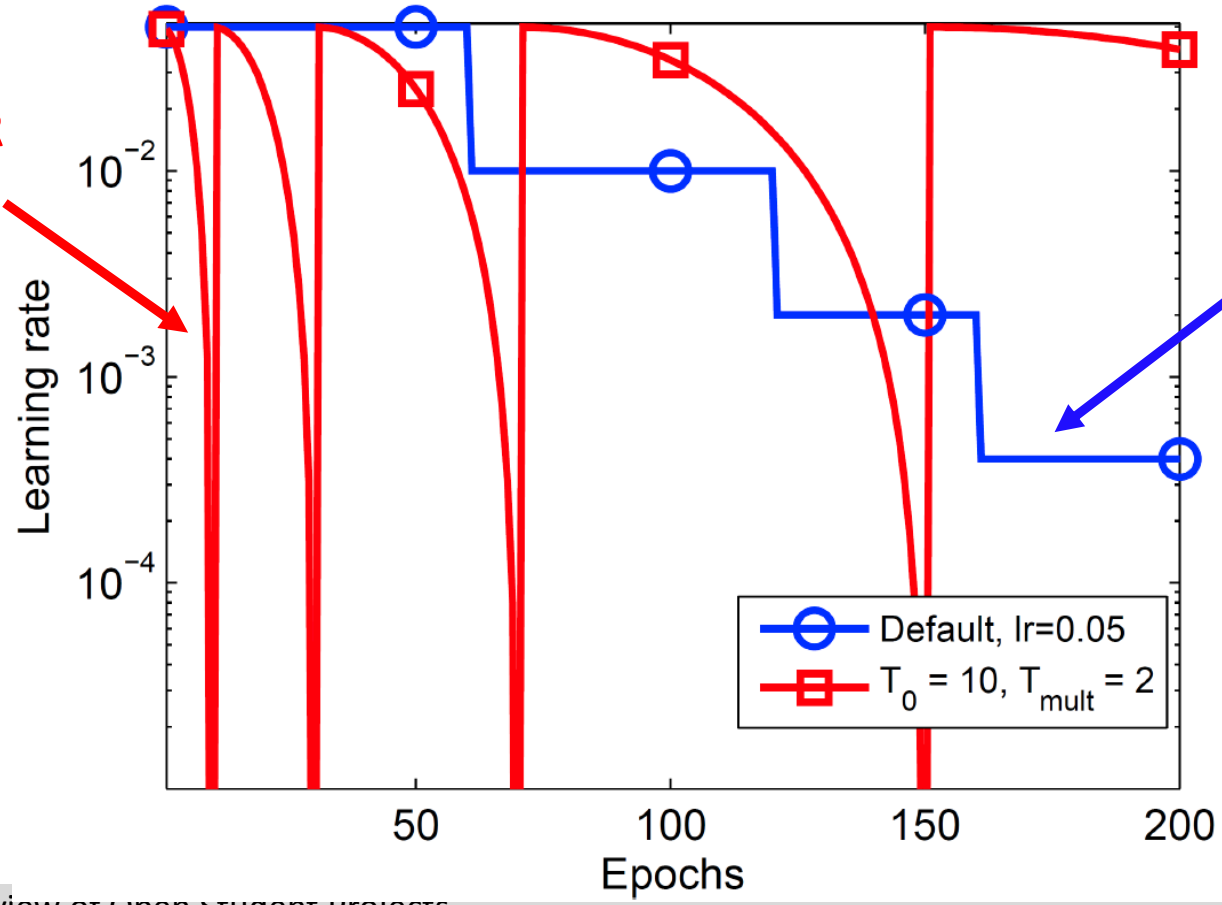
- This is a very important part of deep learning
- But there is no great solution yet; still lots of trial & error
- Better optimizers can be found manually
- It is also possible to use ML techniques to learn better optimizers

Stochastic Gradient Descent with Warm Restarts (SGDR)

[Loshchilov & Hutter, ICLR 2017]

- New Learning Rate Schedule
  - Iterative stages of convergence
  - Each stage following a **cosine annealing schedule**

New SGDR schedule

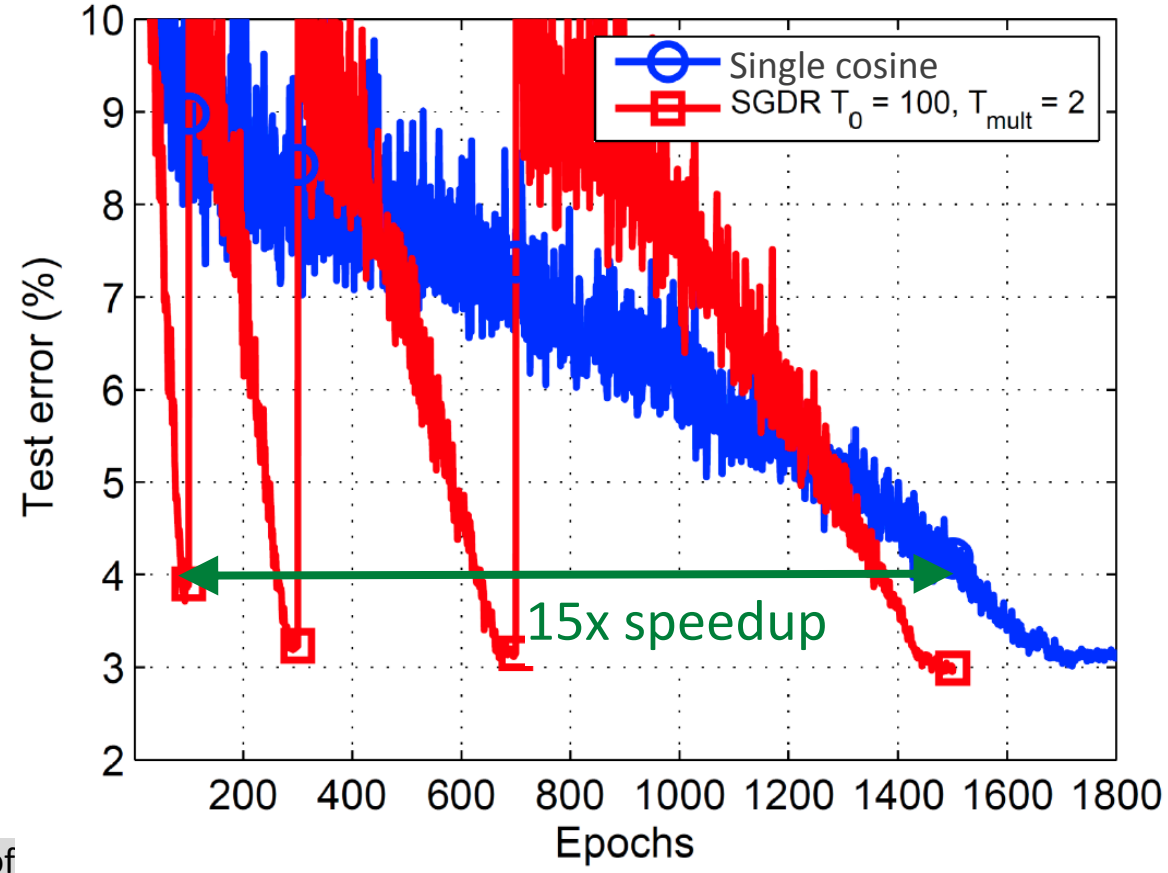


Standard stepwise learning rate schedule

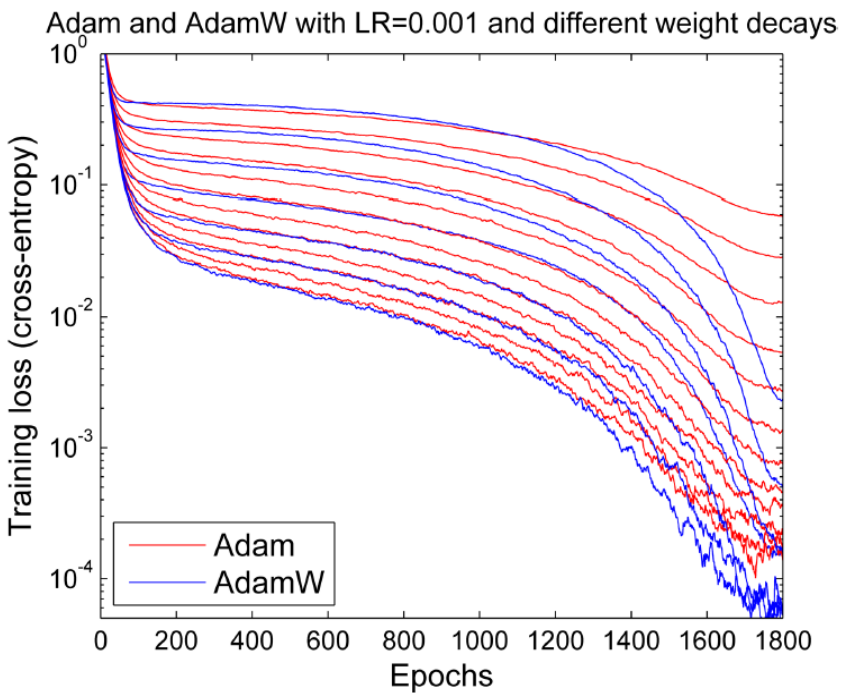
Stochastic Gradient Descent with Warm Restarts (SGDR)

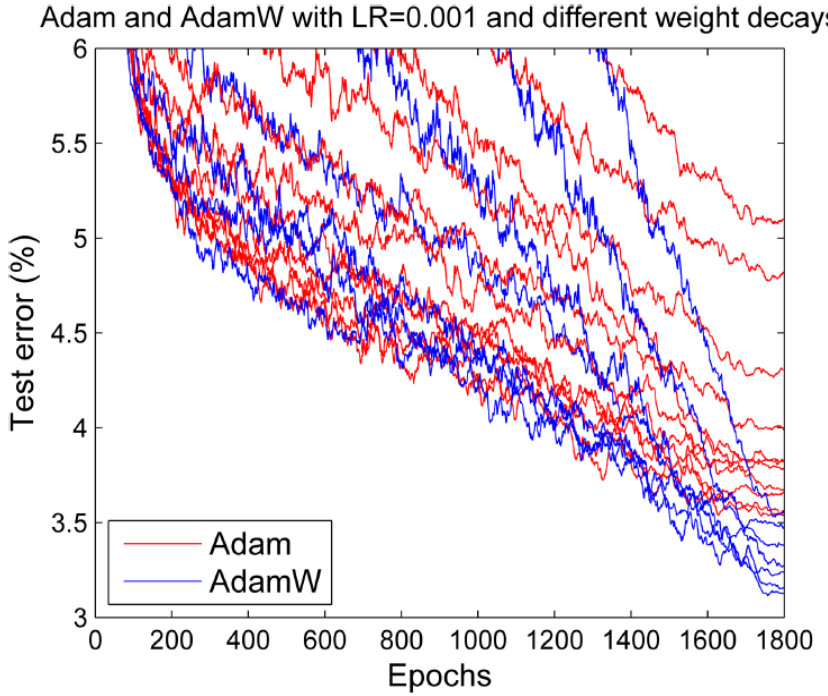
[Loshchilov & Hutter, ICLR 2017]

- Results
  - Cosine annealing is better than other learning rate schedules
  - Final performance of SGDR: similar to single cosine annealing
  - Much improved anytime performance (up to 15x faster)



- Fixing weight decay in Adam
  - Adam: most popular optimizer (> 4000 citations in 2017)
  - We exposed that in adaptive gradient algorithms, L2 regularization != weight decay
    - Standard L2 regularization does not generalize well; weight decay does
    - 20% lower error rates





Projects about Optimizers

- *Why* does cosine annealing work better than the stepwise schedule?
  - When does which schedule work best?
  - This could also involve other tasks, such as RL
- Follow-up on fixing weight decay in Adam
  - Evaluate this approach for more benchmarks
  - Evaluate using both L2 regularization and weight decay
  - Evaluate this approach for the newest versions of Adam / AMSgrad

Optimizing a policy network for Atari

- RL is the main approach for playing Atari
  - See the DQN Nature paper

- Evolutionary strategies are an alternative
  - All we need is a policy network that maps states to actions
  - We can optimize this network by evolutionary strategies
    - Highly parallelizable
    - Well studied
    - OpenAI published a paper about this last year
    - Previous MSc project: showed that even simpler methods work
    - Lots of ideas for follow-up; code base available to start from

7. Learning to Learn / Optimize

- View an optimizer (like SGD, Adam, etc) as a mapping from some state to the next step to be applied
  - Parameterize that mapping as a neural network
  - Use RL or gradient descent to optimize that network

- Project
  - Bootstrap from existing code
  - Can we learn cosine annealing & SGDR?
  - Can we apply this for different hyperparameters (weight decay, etc)?
  - Can we learn an optimizer that is actually better than Adam etc in practice?

7. Learning to Learn / Optimize

- Learning to learn without gradient descent by gradient descent
  - Learns a global blackbox optimizer
  - State: set of points in the space already evaluated, and their performance
  - Action: which point in the space to evaluate next
  - Loss: performance obtained (e.g., in fixed horizon)
  - Policy network, to be optimized with SGD

- Project: reimplement this approach
  - Code is not available

7. Learning to Learn / Optimize

- Learning an entire algorithm component
  - For basically any algorithm; here: a SAT solver
  - Represent the algorithm component as a neural net with the component's output as the network output.
  - Use policy gradient to optimize the network to improve the algorithm's overall performance
  - Expensive in terms of compute time, but (in principle) very cheap to set up in terms of human time

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